Advanced Review

Decision making under risk and uncertainty

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Decision making is studied from a number of different theoretical approaches. Normative theories focus on how to make the best decisions by deriving algebraic representations of preference from idealized behavioral axioms. Descriptive theories adopt this algebraic representation, but incorporate known limitations of human behavior. Computational approaches start from a different set of assumptions altogether, focusing instead on the underlying cognitive and emotional processes that result in the selection of one option over the other. This review comprehensively but concisely describes and contrasts three approaches in terms of their theoretical assumptions and their ability to account for behavioral and neurophysiological evidence from experimental research. Although each approach contributes substantially to our understanding of human decision making, we argue that the computational approach is more fruitful and parsimonious for describing and predicting choices in both laboratory and applied settings and for understanding the neurophysiological substrates of decision making. © 2010 John Wiley & Sons, Ltd. *WIREs Cogn Sci*

Decision making is a faculty that is evident in nearly everything we do. From the commonplace to the consequential, our lives are guided by the decisions we make. Therefore, it is important to understand how we make decisions, so that we may be aware of how various factors may have exerted an influence on past decisions, and so that we may be able to improve upon future decisions. Indeed, one could easily argue that our decision-making ability and the agency it provides us is what separates us from lower order animals.

Because decision making is so central to our lives, it is not surprising that it receives research attention from a wide range of disciplines: cognitive psychology, economics, political science, marketing, social psychology, engineering, philosophy, and more. Although this breadth in contributing disciplines is beneficial in bringing multiple perspectives to bear, it is also (at least partly) responsible for somewhat divergent or inconsistent research goals. Some researchers are interested in how to make the 'best' decision under specific conditions, while others are interested in the explanation for a specific course of action; some prefer to know *what* decision should be made, while others strive to understand *why*. In the current review, we identify three major streams of development in decision theory that can be classified according to the focal behaviors and functional nature of the corresponding decisions.

First, a great deal of foundational decision research was focused on the notion of making 'optimal' decisions. Given a particular situation, how should one go about selecting the best among competing alternatives? This *normative* research stream has the goal of reducing a decision situation essentially to a mathematical optimization problem and finding the correct solution to this problem. It is responsible for treating decision outcomes as random variables, casting decision problems in expectation terms, and deriving solutions that maximize the expected utility among probability distributions of outcomes produced by different actions.

Second, this treatment gave rise to a counterpoise among researchers who wanted to impart a more psychological and constrained view of decision making. Because humans often make 'suboptimal' decisions, how can we describe and predict the choices that one will make in a particular situation? Research with this *descriptive* focus attempts to describe how humans actually make decisions, rather than trying to

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find ideal decisions for any given situation. People are not likely to be able to apply the analytic machinery developed within the normative approach, and the descriptive perspective can be characterized by the addition of psychological factors that embellish this basic machinery. That is, this approach retains a form of the utility maximization goal but is focused on what psychological adjustments need to be made to account for observed human decisions.

Third, beyond providing psychological meaning and justification to descriptive modifications of the normative theories, many recent researchers examine the decision processes themselves, rather than just the final choice. What mental or neural operations are taking place that lead to the selection of one option over another in a given situation? This *computational* approach seeks to understand what the underlying (cognitive and emotional) processes are that produce the observable actions predicted by the descriptive theories. Rather than beginning with utility maximization goals derived from the normative approach, and then modifying them as needed in the descriptive approach, the computational approach is built directly from cognitive and emotional processing assumptions. It attempts to formally define the dynamic processes—whether neural, componential, or holistic—that over time determine a final decision.

This advanced review will provide an update on the status and contemporary research for each of these major research streams. It will provide sufficient background in the development of each approach but focus on how they deal with current issues and challenges in the realm of decision making. It will focus on individual (rather than collective or group) decision making. It will also focus on situations dealing mainly with *risk* in the form of known possible outcomes with well-specified probabilities. These situations are distinct from situations of *uncertainty* involving ambiguity in the probability distribution over outcomes, or situations of *certainty* where choice outcomes are clearly defined. Although these different domains share some similarities, they are treated distinctly in the extant literature; space constraints prevent detailed treatment of each.

NORMATIVE APPROACHES TO DETERMINE 'OPTIMAL' CHOICE

We make many different types of decisions everyday. What should I do this weekend? Should I pay off my credit card or wait? Should I take the job offer or not? Do I take this job or keep looking? Most theories of decision making assume any of these decisions can be abstracted and represented as the selection of a single course of action X described by the value of the possible outcomes $\{x_1, x_2, \ldots, x_n\}$ that could result from selecting the action and the associated probability that each outcome would occur if the action were selected $\{p_1, p_2, \ldots, p_n\}$. This representation reduces the choice task to one of selecting from among competing simple random variables (see Ref 1, for a critique of this 'gambling metaphor', or Ref 2, for an alternative 'naturalistic' research paradigm). The simplest rule, mathematically, is then to select the option X that has the highest expected value EV(X):

$$\mathrm{EV}(X) = \sum_{i=1}^{n} p_i x_i \quad (1)$$

For example, take a decision with two options: (A) a certain outcome valued at \$1 million, and (B) an uncertain option with an 89% chance of \$1 million, a 10% chance of 5 million, and a 1% chance of receiving nothing. The expected value calculation in Eq. (1) suggests that one should take the second option, because $\mathrm{EV}(B) = \$1.39$ million $>$ \$1 million $= \mathrm{EV}(A)$.

The EV rule seems reasonable for gambles played repeatedly many times. But for gambles with high stakes that are only played once, it is easy to see that this objective may not be so appealing. Bernoulli[3] observed that most people did not make choices in line with the expected value rule when the values (x) were determined with large objective amounts (e.g., \$1 million). He proposed that people did not view (monetary) outcomes objectively, but rather they did so subjectively. That is, \$1000 does not have the same subjective value to both a miller and a millionaire—the former places more subjective worth on the same objective dollar amount. In fact, given the hypothetical choice between A and B above, the majority of experimental participants select A even though it has a lower expected value. Presumably, this is due to the fact that the subjective experience of receiving \$5 million instead of \$1 million is not five times as pleasurable as receiving \$1 million instead of \$0. Rather, as wealth increases, the additional value placed on subsequent increments decreases (an additional \$1 million means more if you are broke than if you already have \$4 million).

DIMINISHING MARGINAL UTILITY

The increments in subjective value corresponding to increases in objective value decrease as the initial objective value increases; this is termed as *diminishing marginal utility*. This explains why a raise of \$10,000 per year would be quite meaningful to the average reader, but probably not to Bill Gates. The concept is similar to the Weber–Fechner Law in psychophysics, where changes in stimulus intensity have different psychological sensations depending on the initial magnitude. Mathematically, this is typically represented with a simple power utility function, $U(x) = x^{\alpha}$. This form also allows for describing an individual's risk attitudes with a single parameter: when $0 < \alpha < 1$, the utility function is concave and risk-averse behavior is predicted, whereas a convex function predicting risk-seeking behavior emerges if $\alpha > 1$.

Mathematically, this involves a function that transforms objective value into subjective *utility*, $U(x)$. A simple modification then suggests one should select an option with the highest *expected utility* EU(X):

$$\mathrm{EU}(X) = \sum_{i=1}^{n} p_i U(x_i) \tag{2}$$

Bernoulli's concept is intuitively plausible and could explain actual choice behavior. Furthermore, it is easy to impute psychological meaning on the utility function, such as risk attitudes (see section *Diminishing Marginal Utility*). However, this approach was criticized by some theorists who adhered strongly to the normative approach, because there was no rational foundation for why people should use the EU for choices only played once. In 1944, a seminal book by von Neumann and Morgenstern overcame this limitation by providing an axiomatic foundation for expected utility theory. The original EU theory was restricted to gambles with objectively known probabilities, but Savage[4] is credited with further extending the axiomatic foundation of von Neumann and Morgenstern[5] beyond subjective utility to additionally include subjective probability for uncertain events with no objectively known probabilities, a notion raised earlier by Ramsey[6] and de Finetti,[7] as well as by von Neumann himself. Mathematically, the *subjective expected utility* (SEU) of an option then becomes

$$\mathrm{SEU}(X) = \sum_{i=1}^{n} \pi_i U(x_i) \tag{3}$$

Here, the events are assigned subjective probabilities, π_i. Savage's[4] axiomatization is still considered as a rational theory, as the subjective probabilities were still constrained by the laws of probability. However, it did not take long before additional empirical evidence about human choice behavior challenged SEU on other grounds.

Allais[8] presented people with the choice between A and B introduced earlier, as well as a choice between two other options: (C) an 11% chance of receiving \$1 million, otherwise nothing and (D) a 10% chance of receiving \$5 million, otherwise nothing. Here, the options C and D are created simply by changing a 'common consequence' of an 89% chance at \$1 million in A and B, respectively, to an 89% chance at \$0. If one chooses A over B in the first choice, then this implies a utility function that predicts one should still take option C over D, because SEU(A) > SEU(B) implies SEU(C) > SEV(D). However, although most people select A instead of B, they select D instead of C. This choice pattern is inconsistent with SEU, regardless of the form of $U(x)$. Specifically, it violates one of the axioms (independence) set forth by von Neumann and Morgenstern[5] and Savage.[4]

This empirical inconsistency prompted researchers to explore further modifications to the SEU framework. At this point, although the basic algorithm was retained (maximization of a mathematical expectation), theories began to depart substantially from these previous 'rational' ideals in order to explain the decisions of we 'irrational' humans.

Another important advance in utility theory was the extension of the theory to outcomes described by multiple conflicting attributes.[9] For example, when choosing a medical insurance plan, one needs to consider not only the cost of the plan but also the breadth of the coverage, the quality of the care provided by the coverage, and other attributes of the plan. Thus this decision involves evaluating consequences with respect to several conflicting objectives. Should one spend more money to achieve greater coverage or should one save money but take a risk with lower coverage? The most commonly used multiattribute utility model combines the values of the conflicting attributes according to a weighted additive rule (much like the utility theory for gambles), where the weights reflect the tradeoffs among the attributes. The weighted additive rule is considered to be a compensatory rule which allows deficits on one attribute to be compensated by advantages on other attributes.

DESCRIPTIVE APPROACHES TO EXPLAIN OBSERVED CHOICE

Descriptive theories in decision making, as their name suggests, are more concerned with describing the choices people actually make rather than providing a 'rational' basis for making choices, as EV, EU, and

SEU aimed to do. This shift is due, in large part, to the fact that psychologists began to relax the idealistic models heretofore introduced by mathematicians, statisticians, and economists. The most popular descriptive theory of choice is termed as prospect theory, introduced by Kahneman and Tversky.[10]

Prospect Theory

Prospect theory introduced four important aspects from cognitive psychology to impart a more human-centered view of decision making.[10] First, it suggested a predecisional 'editing' stage where the decision problem is prepared, such as by eliminating clearly inferior choice options and simplifying and mentally ordering outcomes. Second, it introduced the notion of *reference dependence*, where outcomes are not evaluated absolutely but relative to some benchmark, such as one's current wealth or 'status quo'.[11] Third, it suggested that outcomes could be evaluated differentially based on whether they were seen as gains or losses relative to the status quo—that is, there were separate utility functions for gains $U_G(x)$ and losses $U_L(x)$. Fourth, specifically, it proposed the concept of *loss aversion*, that the marginal utility of a constant change is greater for losses (a \$100 loss is more aversive than a \$100 gain is pleasant).

Formally, these assumptions can be incorporated into Eq. (3) with the appropriate specification (Figure 1): $U_G(x) = f(x - S)$ for $x - S > 0$ and $U_L(x) = -\lambda f(S - x)$ for $x - S < 0$ where S is the status quo and f is concave for gains, convex for losses, and steeper for losses (λ is a parameter to model the degree of loss aversion). Kahneman and Tversky also introduced the term *decision weight* for the multiplier attached to each outcome. Although they assumed decision weights were based on the objective probabilities, $\pi(p)$, they explicitly distinguished this notion from a purely probabilistic evaluation.[12] They put forth a strictly convex form for $\pi(p)$ that implied overweighting of small probabilities and underweighting of large probabilities; a revised form suggests concavity for small probabilities (Figure 1).[25]. These restrictions on Eq. (3), spurred by reflecting on human thinking rather than any rational calculus, produced a theory that was much more accurate at describing actual choices—but only to a degree.

SUBJECTIVE PROBABILITY AND UNCERTAINTY

Prospect theory introduced the important notion of decision weights, but this in turn raises the question of how these weights are psychologically determined.

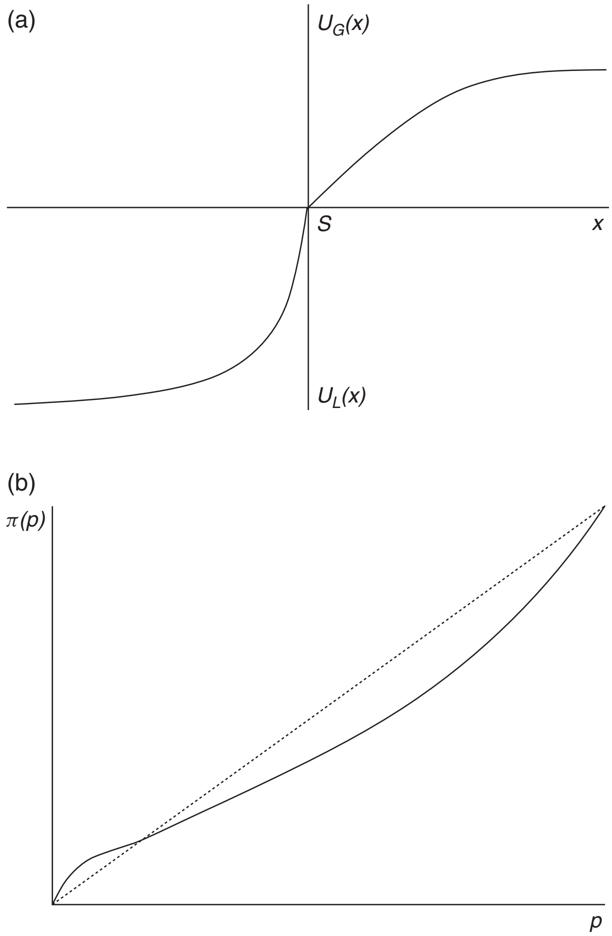

FIGURE 1 | Cumulative prospect theory's value and weighting functions.

Kahneman and Tversky[10] introduced the probability weighting function, which could be interpreted in terms of concepts such as discriminability and attractiveness,[13] or affective notions such as elation and disappointment.[14] Computational models of decision weighting describe how these weights may result from probability judgments based on memory retrieval[15] or as the result of differential attention and 'dwelling' on specific outcomes or events.[16]

Craig Fox's extension of support theory to decision making[17–19] describes how individuals in circumstances of uncertainty might estimate probabilities, which in turn can then be used to derive decision weights. Support theory distinguishes among different descriptions of events as the carriers of belief (rather than the objective events themselves) and is based on support for a focal or salient description relative to other possible descriptions. This is an important theory for extending decisions under risk (known event probabilities) to situations of uncertainty (unknown event probabilities).

Rank-Dependent Theories

Even prospect theory was unable to account for all the observed trends in human choice behavior.[10,20,21] For example, it predicted that people would choose options even if they were clearly dominated by other options in the choice set (see Ref 22, for a review) and was severely limited to choice options with only two outcomes. It also implied that the weight given to an outcome was independent of the value of the outcome. That is, the weight given to a probability of 0.10 would be the same regardless whether this probability corresponded to the worst or the best outcome of a gamble, which is not true for human choices.[23]

In the late 1980s, several researchers independently arrived at an idea that served as the next major modification to the expected utility framework. In particular, it allowed the decision weight of an outcome to be dependent on the rank order of the outcome (e.g., whether it was the worst or the best), and hence these theories are called *rank-dependent utility (RDU) theories* (see also rank-and-sign-dependent utility in Ref 24). This was achieved by changing the basis of the weighting function from the probability of winning x to the probability of winning x *or more* (decumulative probability). Tversky and Kahneman[25] extended their original theory into *cumulative prospect theory*, perhaps the most popular RDU theory. Formally, RDU theories propose the following general function for the decision weight assigned to a positive outcome x_j:

$$w(x_i) = \pi\left(\sum_{i}^{n} p_j\right) - \pi\left(\sum_{i+1}^{n} p_j\right) \tag{4}$$

A notational change produces the following overall utility of an option X:

$$\mathrm{RDU}(X) = \sum_{i=1}^{n} w(x_i)U(x_i) \tag{5}$$

RDU theories, via Eqs (4) and (5), introduce a subtle but important distinction between the subjective probability and the decision weight. The subjective probability refers to the distortion of decumulative probability, $\pi(\cdot)$, and is thus essentially a psychophysical measure. Decision weight, $w(\cdot)$, is a further transformation that describes the relative weight given to an outcome when integrating across other outcomes to determine the holistic value of an option. In earlier SEU models, the decision weight was simply equal to the subjective probability, $w(p) = \pi(p)$.

Configural Weight Theories

Michael Birnbaum and his colleagues advocate a descriptive theory that is similar in some respects to RDU theories, but incorporates important differences and makes competing predictions regarding some important empirical phenomena.[26,27] For example, RDU theories predict that individuals should never choose an option that is stochastically dominated by another. If we define X_Q as the random value produced by gamble Q and X_R as the random value produced by gamble R, then option Q stochastically dominates option R if and only if $\Pr(X_Q > x) \geq \Pr(X_R > x)$ for all x, and the inequality is strict for at least one x (i.e., the cumulative distribution function of Q is always above that of R). In fact, for certain gamble types, people seem to robustly select an option that is stochastically dominated by another option in the choice set.[27]

Birnbaum's *configural weight utility* (CWU) theories are able to explain these violations of stochastic dominance, as well as the other behaviors covered previously. CWU theories retain the algebraic representation and expectation maximization rule of all previous utility theories. The key difference is in the specification of the weighting function, which is exemplified by the transfer of attention exchange CWU model (TAX; see Ref 28). In the TAX model, similar to the RDU models, lower values of a gamble 'steal' or 'tax' decision weight from higher values. But in addition, the TAX model assigns a separate weight to each outcome listed in a gamble even if the same value is listed more than once. For example, the single weight assigned to \$100 for the gamble '0.5 chance to win \$100 or else win nothing' is not the same as the total weight assigned to both of the \$100 outcomes in the gamble '0.25 chance to win \$100, 0.25 chance to win \$100, and 0.5 chance to win nothing'. RDU theories assign weight based on the cumulative probability of an outcome, and so these two gambles would be treated as the same. The violations of stochastic dominance indicate that people do not treat these gambles as the same.

HISTORICAL PERSPECTIVES ON CONFIGURAL WEIGHTING

The configural weight models formally applied to decision-making behavior are found as early as Birnbaum and Sutton.[29] However, it is notable that the idea of configural weighting can be traced back even earlier to explanations of social judgment biases in Birnbaum and Stegner,[30], based on work by Birnbaum et al.[31] Thus, configural weighting theories actually predate both the decision-theoretic work on rank-dependent weighting functions and even prospect theory.

Regret Theory

Prospect theory, RDU theories, and CWU theories strove to incorporate human tendencies into the evaluation of outcomes and their associated probabilities, or weights. Other theories sought to redefine the basic currency of a choice option, such as by introducing utility derived not just from the actual outcome values, but also by comparisons to outcomes of foregone options.[32,33] Loomes and Sugden[33] introduced their regret theory in response to prospect theory and showed how it could explain the same empirical results put forth by Kahneman and Tversky[10] as evidence for the latter. Essentially, regret theory assumes that utility $U(x)$ is composed of two distinct components, an evaluation of the outcome that is obtained and a difference between that outcome and those forgone.

For example, assume one is choosing between two gambles, A and B, determined by a coin flip. If one chooses A, then \$100 is won if the coin lands on heads, and nothing is won if it lands on tails; B offers \$70 for heads and \$30 for tails. In evaluating option A, regret theory proposes that the utility assigned to the outcome 'heads' will be a (linear) combination of the utility of \$100 and the additional utility or 'rejoice' associated with the fact that, had B been chosen, then only \$70 would have been won. Conversely, evaluation of the outcome 'heads' for option B involves the utility of \$70 as well as the disutility or 'regret' associated with the fact that one could have obtained \$30 more had A been chosen. The basic psychological mechanisms involved in regret theories are similar to those studied extensively in other psychological domains, such as work in social psychology on counterfactual thinking.[34] Mellers et al.[35] extended these ideas and developed a more detailed model of the emotional basis for these regrets.

Security-Potential/Aspiration Theory

Lola Lopes introduced additional psychological constructs such as hope, fear, and goal achievement to develop a descriptive theory of decision making called security-potential/aspiration (SP/A) theory.[36,37] This theory assumes that a decision maker simultaneously considers two distinct criteria in making decisions. First, one considers a utility component similar to those found in RDU theories. However, Lopes allows for evaluation of outcomes in both a low-to-high, cumulative fashion and the decumulative, high-to-low fashion posited by RDU theories. Her reasoning is that individuals may exhibit security-minded behavior that focuses on the probability of obtaining an outcome with a value of *x or less*, and/or a potential-minded analysis in line with RDU that focuses on the probability of obtaining an outcome with a value of *x or more*. Mathematically, Lopes allows for a parameter that moderates the degree to which the security-minded versus potential-minded analyses contribute to the assessment of outcome utility.

Second, SP/A theory includes the notion of an aspiration level or goal achievement component. That is, in addition to the value assigned to options based on the assessment of their outcome value (as described in the preceding paragraph), options are evaluated favorably if they allow a decision maker to achieve some preset goal. Mathematically, this aspiration criterion evaluation for an option is based on the probability that the option provides an outcome at or above the aspiration level. If one has a goal of winning \$80 in the coin flip choice from the previous section, then A has a 50% chance of meeting this aspiration level (corresponding to the 'heads' value of \$100 > \$80) and B has no chance of meeting the aspiration level (neither outcome is >\$80).

SP/A theory assumes that a decision maker integrates the two components into a holistic utility value for each option and again maximizes the expectation of this utility. Each single component may produce competing predictions that produce internal conflict. For example, with an aspiration level of \$80, A is preferred using the goal criterion; however, a security-minded decision maker who focuses on the low outcomes may prefer option B on this criterion (due to its advantageous low outcome, relative to A). Mathematically, model parameters can specify the relative degree to which each component contributes to choice behavior.

COMPUTATIONAL APPROACHES TO MODEL LATENT CHOICE PROCESSES

Descriptive theories of choice embellish the basic framework of maximizing an expectation with observations from human psychology. Prospect theory, RDU theories, and CWU theories make claims about the specific nature of utility and probability assessment that depart from rational norms and laws of probability. Other theories include additional considerations beyond an expected utility assessment, such as the potential satisfaction or disappointment resulting from comparing outcomes to those forfeit (regret theory), or the desire for a choice option to fulfill some goal (SP/A theory). In contrast to all of these descriptive approaches which focus on choice as determined by the maximization of some utility function, computational approaches focus on the underlying cognitive, motivational, and emotional processes from which choices dynamically emerge. In this section, we will review several popular research streams that adhere to this philosophy.[38]

PROCESSING ASSUMPTIONS AND MODEL REPRESENTATION

Computational models do not begin with the algebraic utility maximization assumptions of the normative and (most) descriptive approaches. However, it could be that choices in line with the normative goals of utility maximization evolve from the underlying processes. If so, it could be that utility maximization is indeed representative of human choice behavior, even if the algebraic representation is merely paramorphic—thus, computational and descriptive approaches are not mutually exclusive.

Heuristic and Rule-Based Approaches

Perhaps the most intuitive computational approaches specify simple procedures for making choices, often called *heuristics*. Heuristics are typically expressed as verbalizable rules or flowcharts for applying discrete steps to make a decision (see Ref 39, for a review and organizing framework).

Elimination by Aspects

One of the earliest popular heuristics was Tversky's[40] elimination by aspects (EBA) model. Consider for example the problem of buying a new digital camera. This is a multiattribute decision involving the consideration of attributes such as price, resolution of the camera, size of the camera, etc. Rather than maximizing a weighted average of attribute values, as suggested by multiattribute utility theories, the EBA model proposes that individuals sequentially consider different aspects, such as whether the price is within budget, whether the resolution is satisfactory, and whether size is sufficiently small for a new digital camera. The probability of considering an aspect is proportional to its importance, so that if price is the most important attribute to a consumer, it is most likely to be considered first.[a] When considering an aspect, any choice option that does not meet a minimum criteria (e.g., a price over one's budget of $300) is eliminated from the choice set and not considered any further. This sequential aspect selection and elimination process continues until only a single choice option 'survives'. Tversky[40] illustrated the ability of this model to account for violations of rational choice axioms (e.g., violations of independence from irrelevant alternatives; see Ref 41 for discussion). Although Tversky[40] also showed how EBA could be represented as a (random) utility model, it has a decidedly different flavor through its presentation in terms of simple rules and is not 'rational' in the sense that it is noncompensatory. An option can be eliminated from consideration simply on the basis of a single attribute even though it may be holistically the 'best' because of its many advantages on other attributes.

Thorngate's Heuristics for Gamble Forms

Thorngate[42] proposed 10 distinct decision heuristics, based largely on the work of Coombs et al.[43] that were formulated for application to choices among gambles like those presented earlier. For example, his minimax heuristic selects the alternative with the highest minimum outcome value, or max$[x_1]$, and the maximax heuristic chooses according to max$[x_n]$. His least-likely heuristic chooses the alternative with the lowest probability of its worst outcome, min$[p_1]$, whereas the most likely heuristic chooses according to max$[p_1]$. Other suggested heuristics include elimination heuristics like EBA, and an equal-weighting heuristic that selects based on the highest average outcome value (ignoring probabilities; see also Ref 44). Thorngate's analyses showed that these simple heuristics often selected options that were normatively optimal (in terms of expected utility) or very close to it.

The Adaptive Decision Maker Hypothesis

Payne et al.[45,46] proposed that decision strategies, including utility maximization algorithms as well as simple heuristics, could be formalized in terms of what they called elementary information processing (EIP) units, such as 'retrieve', 'add', 'multiply', and 'compare'. Implementing maximax among two alternatives A and B would involve four EIPs: retrieve a_1, retrieve b_1, compare a_1, b_1, choose max $[a_1, b_1]$. This specification welcomes precise implementation in computer simulations and allows for the derivation of measures such as decision time and information acquisition. It is worthy to note that, although Payne et al.[45,46] did not introduce novel heuristics *per se*, their method of formalizing and studying heuristics has been enormously influential on subsequent computational modeling. Furthermore, they introduced an adaptive view of strategy selection, based on an efficient frontier involving a tradeoff between desired levels of effort (in terms of EIPs) and accuracy (relative to a normative algorithm). This represents an important advance in understanding which heuristic from among many may be applied in any given situation.

Gigerenzer's Adaptive Toolbox

Gigerenzer and Todd[47] and the ABC Research Group also advance the notion of a collection of decision heuristics. Many of their heuristics are very similar to the earlier mentioned heuristics in terms of the process description. For example, the priority heuristic[48] involves sequential application of *thresholded* versions of the maximin, most-likely, and maximax heuristics. First, choose the option that maximizes the minimum possible outcome; but only if the minimum outcome value is sufficiently larger than the other options' minimum outcomes. Otherwise, consider the probability p_1 of each option's lowest outcome, and so on. Although the actual heuristics are very similar to those already mentioned, this research stream is notable for three additional characteristics. First, it is applied to prediction, inference, and categorization, as well as decision making. Second, like Payne et al.,[46] it stresses the adaptive nature of the development and application of simple heuristics (hence the term 'adaptive toolbox') in terms of ecological fit between the heuristics and the environment. Third, they decompose the majority of their heuristics into three distinct components: a rule for guiding information search, a rule for determining when to stop search, and a decision rule applied to the information collected. This strikes a balance between the low-level EIP-based description and the presentation of holistic rules.

Decision Field Theory

The most influential type of decision model in cognitive science is the sequential sampling/accumulation model. This type of model has been applied to neuroscience, sensation, perception, memory, and categorization domains.[49] The first application of sequential sampling models to decision making under risk and uncertainty was decision field theory (DFT; Refs 50–53, for reviews; see also Ref 54, for a neural network representation of DFT). Most broadly, DFT is a mathematical model based on cognitive principles of selective attention and relative evaluation, that models deliberation as a dynamic system accumulating evidence in favor of each choice option. The first option to reach a criterion level of evidence is selected. In contrast to descriptive utility theories, DFT thus makes specific quantitative predictions about information acquisition and response times, in addition to choices.

First, DFT assumes that attention shifts to different dimensions of the choice task over time. For gambles, these shifts occur (independently) across the outcomes of each option, with the probability of attending to an outcome proportional to its objective probability (see Ref 16, for details). For preferential choice, these transitions are typically assumed to be defined across attributes, with the simplifying assumption that attention to a specific attribute (e.g., the price of all camera models) at any moment is proportional to the attribute's importance[51] (see Ref 55, for alternative assumptions).

Second, the current focus of attention generates a relative evaluation for each choice option. When price is under consideration, then those options with the highest prices will receive low evaluations. Specifically, an option's evaluation is based on the affective reaction to the option's value on the focal attribute, relative to the average reaction of all the other competing options' values.

Third, these momentary evaluations are accumulated over time to describe the current preference for each option at each point during deliberation (Figure 2). To the extent that attention focuses on features that are favorable for a particular option, that option will have a greater value of preference over time. This accumulation process can be subject to specific effects such as gradual decay to produce recency effects, as well as inhibitory influences from competing options (i.e., as one option becomes preferred, it inhibits or reduces the preference for other similar options). An option is chosen, ending deliberation, when it reaches a preset threshold level of preference used as a criterion for being 'good enough' to merit selection.

DFT has been successful in accounting for various puzzling phenomena in pairwise choice between gambles under risk and uncertainty,[50] as well as robust paradoxes arising in multialternative and multiattribute choice problems[51] and pricing.[56] It provides a measure of preference strength (rather than just direction) and has recently been extended to predict decision confidence as well.[57] It also uniquely accounts for effects of decision time such as speed–accuracy tradeoffs[50] and changes in preference under time pressure.[58] DFT has also been extended to model rule learning and rule-based decision making, including strategy switching.[59] It has been successfully applied to engineering problems such as human-in-the-loop control systems[60] and agent-based models of emergency evacuation decisions.[61]

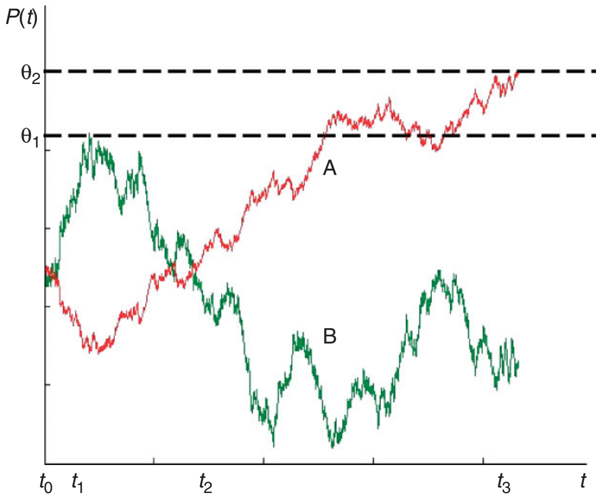

FIGURE 2 | Decision field theory (DFT) representation of preference accumulation for two options. Preference *P(t)* accumulates for each option, shown as separate trajectories, over time *t*. At time t_1, option B is preferred with a higher value of *P(t)*; at time t_2, preference is equal between the two options, after which option A is consistently preferred. Choice is determined when an option's trajectory reaches the threshold level of preference, $P(t) = \theta$. A decision maker with a threshold of θ_2 would thus select option A at time t_3; a more impulsive individual modeled by θ_1 would select option B at time t_1.

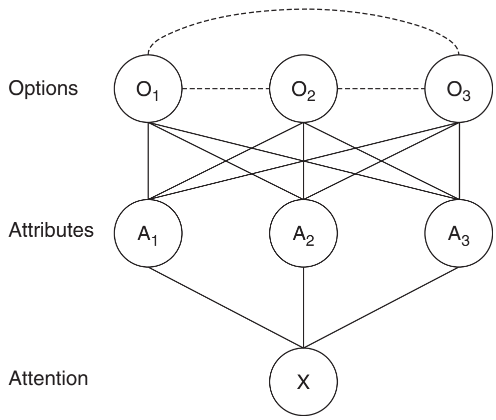

FIGURE 3 | Generic neural network representation of a decision problem. Each of three choice options is described by three attributes. An attention node determines which attribute(s) is/are processed at each time step and thus embodies decision weight. Links between attributes and options represent the value of each option on the corresponding attribute. All solid connections are assumed to be bidirectional for parallel constraint satisfaction (PCS) models, and feedforward for leaky competing accumulator (LCA) and decision field theory (DFT). Inhibitory bidirectional connections among options (dashed lines) model competition among options in LCA, PCS, and DFT models. LCA and DFT assume an additional layer between options and attributes to compute differences.

Connectionist Approaches

Several contemporary computational models of decision making besides DFT have been cast in neural network architectures. While these models may be less transparent and in some sense more complex, they are popular in many cognitive domains and have the advantage of neurally plausible mechanisms (Figure 3).

Leaky Competing Accumulator Model

Usher and McClelland [62] proposed a connectionist model that employs a recursive network to describe how preference builds for various choice options over time. This model is very closely related to DFT (see Ref 63, for a comparison of the two). It also involves sequential comparison of attributes where the options 'compete' for preference based on their relative excellence, and these momentary comparisons are 'accumulated' over time into a holistic preference value for each option, with some degree of decay (or 'leaking'). In contrast to DFT, it includes the notion of loss aversion from prospect theory as a fundamental assumption.

Coherence-Seeking Network Models

Thagard and Milgram[64] applied Thagard's network model called ECHO to decision making, and other researchers have since extended this formulation.[65–67] Most recently, Andreas Glöckner et al.[68,69] have successfully applied one of these parallel constraint satisfaction (PCS) models to various decision-making tasks. PCS models involve a search for coherence or consistency among a set of choice options, such as in trying to resolve conflicting preferences across options (one option may have a lower price, but another has better resolution, and so on). Upon presentation of a choice problem, PCS mechanisms are activated to find the best interpretation of the problem in a perception-like process. Rather than explicitly describing any necessarily conscious strategy or heuristic that is applied to a choice problem, these models rely on a more holistic or Gestalt conceptualization where a preferred option 'emerges' instantly or over the course of deliberation.

Choice options and outcome values are represented as network nodes, and links represent the possession of certain aspects as well as their decision weight (based on link strength; see (Figure 3). The basic intuition is that there are some sets of node activations (option preference strengths) that will produce a stable network (consistent representation), based on the constraints in the form of attribute values and weights. Given the decision problem representation, initial advantages of one option are automatically highlighted by increasing the activation of supporting and decreasing the activation of contrary information.

An activation updating algorithm continues to adjust the node activations until a stable state is achieved, at which point the node (choice option) with the highest activation is predicted to be chosen. Importantly, these models involve bidirectional links between attributes and options and are thus able to explain 'restructuring' of the choice problem,[70,71] such as changes in attribute importance or decision weight across the choice task (i.e., coherence shifts) that are not possible in static, descriptive approaches.

Memory-Based Approaches

Several researchers have acknowledged the crucial role that memory plays in decision making.[72,73] In fact, simple recognition memory can be used to make inferential decisions when the likelihood of recognition based on salience is correlated with the decision criterion.[74] Dougherty et al.[15] use a memory-based judgment model to account for several robust phenomena in judgment and estimation tasks, such as base-rate neglect, hindsight bias, and the conjunction fallacy.[75] Elke Weber, Eric Johnson, and colleagues also propose that memory processes can be used to model decision tasks.[76,77] This approach, most recently dubbed 'Query theory', assumes that preferences that drive choice and other decisions are based on a collection of serially posed queries to memory concerning relevant characteristics of the task. For example, if deciding whether to buy a certain digital camera, an individual might attempt to recall experiences with similar models or generate the pros and cons of buying the camera. Query theory is able to explain some empirical trends in human decision behavior by embellishing this simple notion with what is known about human memory, such as serial position effects, priming, and interference. Although the theory's assumptions have been empirically supported, at this point it has not been formally introduced as a mathematical model or at a specific algorithmic level, as the preceding computational models have.

SUMMARY AND FUTURE DIRECTIONS

We do not propose that any of the approaches described above is privileged in any objective sense. Rather, each approach may be seen as possessing inherent strengths and weaknesses, or as differentially applicable across domains or academic pursuits. The class of utility models born from the normative approach has the appeal of an axiomatic foundation, meaning that adherence to specific principles ensures that a utility representation can be created to describe and predict their choices.[24] This allows for a strict and concise way of expressing a decision policy, and lends itself to easy derivation of closed-form predictions. The problem arises when individuals or people in general fail to adhere to these principles. Computational approaches benefit from increased attention to mental and emotional processes and thus psychological plausibility. They can also account for many of the violations of these principles and often of collections of violations. However, these models are less transparent and thus often more difficult to treat analytically, often requiring simulation or direct application to a specific context to derive predictions. Finally, both within and across classes of models, it is important to understand the tradeoff between flexibility and robustness of models. For example, does the increased predictive power of prospect theory over earlier SEU theories justify the 'cost' of increasing the number of free parameters? Furthermore, is the increase in fit to the data theoretically meaningful above and beyond that afforded by this increased flexibility (see Refs 78–80, for excellent discussions of these issues)?

This review has provided a comprehensive but concise account of the development of theories in decision making under risk and uncertainty. Although decision research has come a long way, there are still many open questions that are not fully addressed, even by the more sophisticated theories covered in this review (see Ref 81). How independent are evaluations of attributes and/or alternatives? Is the evaluation of probability (or weight) separable from the evaluation of outcome value? Furthermore, this review is not exhaustive of the theories and approaches in decision research. For example, an entire class of random utility theories[82] is beyond the scope of this review, as are some of the more recent computational models. A 'dual systems' approach recognizing the role of automatic or intuitive processes, in addition to more directed and deliberative processes, is also becoming quite popular[83–85] (see Ref 86 and the related commentaries for various perspectives; and Ref 87, for the historical precedent in cognitive science). Finally, the field has relatively recently focused a great deal on understanding the role of affect or emotion in decision making[35,88–90] (see Ref 91, for an earlier treatment).

An important recent development in decision research is the advent of neuroscientific methods to better understand decision making under risk and uncertainty (see Ref 92, for a concise review and organizing framework; for more extensive summative treatment, see Refs 93,94). In fact, this has spawned an entire 'subfield' called neuroeconomics or decision neuroscience that attempts to verify the underlying neural substrates associated with the various components of decision theories and their purported mechanisms.[95] Work in this vein has indeed found evidence for brain regions responsible for representing the components of utility theories such as probability and reward value[96] (see Ref 97, for a discussion), as well as evidence for distinctions between gains and losses consistent with prospect theory.[98] Although this work supports the necessary condition of an adequate neural representation underlying utility theories, it is not sufficient evidence for the maximization goal process. That is, there is evidence for the ingredients of utility theories, but not necessarily for the mechanism that uses this information to produce choice (action selection).

There is now substantial neurophysiological evidence supporting the mechanisms hypothesized by computational accumulation models such as DFT and leaky competing accumulator (LCA) (see Refs 99,100, for reviews). Specifically, recent research indicates that neuronal activation accumulates over time during decisions under risk and uncertainty, and an action is performed when the accumulated evidence surpasses a threshold.[94,101,102] Thus, in contrast to the normative and descriptive utility maximization theories, there is considerable neuroscientific evidence for neuronal populations that may be responsible for the computational process that produces observable decision behavior.

In closing, we would like to convey the excitement and opportunity that face the field of decision making. Current advances are beginning to produce fruitful practical results. For example, prospect theory has impacted economic theory, and computational models (heuristic rule-based models and dynamic accumulation models) are being incorporated into engineering and agent-based models of mixed human and machine systems. The number and nature of tools at our disposal continue to grow (including experimental techniques for process tracing; see Refs 45,46,103), as does the number and nature of fields involved in studying decisions. As they do, we hope to better understand how people make decisions, predict what decisions might be made in given situations, and reflect and improve upon those already made.

NOTES

[a]Note that this model is closely related to the earlier lexicographic models of Coombs[104] and Fishburn.[105] These models, however, specified a deterministic order for attribute selection.

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